Research Proposal of the Thesis Entitled

Feasibility Study of Three Layered Ensembled Learning Model for Gliomas Grade Classification

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By

Arvind Singh

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202406010001

Under the guidance of Dr. Gaurav Londhe

in the

Unitedworld Institute of Technology

Karnavati University, Gandhinagar

1. Introduction

Correctly classifying gliomas, one of the most common and aggressive forms (and their associated molecular tumors) is important for selecting appropriate treatment to improve patient outcomes. While Magnetic Resonance Imaging (MRI) is a popular non-invasive diagnostic tool for diagnosing glioma, manual diagnosis is subjective and subject to variability. Why? Radiologists can benefit greatly from automated classification systems as they can provide consistent and precise assessments. However, the complexity and heterogeneity of gliomas often make it challenging to describe them in individual models. The study suggests a three-layer ensemble learning model for glioma grade classification using the BraTS 2020 dataset, which addresses these difficulties. The model proposed is a combination of deep learning and traditional machine learning techniques.

A smart aggregate substance forms the second layer of the system. The decision layer produces a reliable and efficient output which serves as the ultimate classification. Ensemble learning allows for the reduction of individual model limitations which leads to improved accuracy and generalization. With the help of this proposed model, medical professionals may get more confidence to adopt the automated system in their practice. Adopted models will show their effectiveness over the state of art that has been adopted for the classification so far. Furthermore, it also confirms the model robustness that elevates the AI system for glioma grade classification that helps to improve the patient care.

Generally, MRI scans include the four different modalities such as T1-contrast, T1, Flair and T2 weighted images. These images are responsible for the gliomas grade classification. To get the effective and accurate grade classification it is important to learn these images and combine their significance to reach the appropriate grade classification. It is always a challenge faced by the researchers to combine them in an effective manner that derives accurate classification. There are so many algorithms that have been developed based on these modalities for gliomas grade classification. The main hurdle for model learning is the dependency of large, annotated datasets. Most of the time data is not available due to their security concerns. With the help of data augmentation techniques small dataset problems can be solved.

In this research model interpretability will be assessed that provide the grate help to the clinicians. It will also provide clear explanation for the decision-making process that creates a high impact on the clinician to trust on AI powered decisions.

Method for model creation:

The proposed model consists of three layers:

- Base Layer: This layer consists of different learning models that are trained on identified datasets.
- Meta Layer: Meta layer classifiers are used for classification that fetch the inputs from the base layer prediction.
- Decision Layer: A final decision-making mechanism to output the glioma grade.

2. Key objectives:

Objective 1: Determine the feasible dataset for ensemble learning approach.

Objective 2: Framing a layered architecture for proposed method.

Objective 3: Implementation of designed framework.

Objective 4: Examine the overall performance of diversified models.

Objective 5: Improve Model Explainability and Interpretability.

Objective 6: Analyze the performance of proposed model.

3. Aim:

This work aims to build a reliable and interpretable three-layer ensemble model to grade gliomas using BraTS 2020. By combining different models, using a meta-classifier to post the results and using explainability methods to make the results clearer, we want to improve the accuracy and practicality of glioma diagnosis in clinics.

4. Review of Literature:

This review focuses on the recent advances in studying brain tumors using deep learning and ensemble techniques. While there has been considerable progress in the field of segmentation tasks, relatively few recent studies have focused on glioma grade classification using such an alternative form of model as the three-layer ensemble model. This review covers the latest advancements in brain tumors using deep learning and ensemble methods. Although there has been much progress in segmentation tasks, only a few have recently explored the three-layer ensemble model for glioma grade classification. This work aims to fill these gaps by combining different models and using a meta classifier to boost accuracy.

Reference No.	Year	Authors	Methods Used	Results	Research Gap
1	2017	Kamnitsas, K., et al.	3D Convolutional Neural Networks (CNNs)	Achieved state-of-the-art results in brain tumor segmentation using BraTS dataset.	Focused on segmentation rather than glioma grade classification.
2	2018	Isensee, F., et al.	Multi-Model Ensemble	Enhanced segmentation accuracy using multiple deep learning models.	Did not explore classification tasks or apply a meta-classifier.
3	2020	Zhou, M., et al.	Radiomics and Machine Learning (Random Forest, SVM)	Improved glioma classification accuracy using radiomics features.	Lacked integration of deep learning models for feature extraction.
4	2021	Chen, J., et al.	Vision Transformers (ViTs)	Demonstrated strong performance in medical image segmentation using ViTs.	Did not investigate their application for glioma grade classification.
5	2022	Lakshminarayanan, B., et al.	Deep Ensemble Learning	Improved segmentation using ensemble techniques.	No application in glioma grade classification using a decision-layer approach.
6	2023	Smith, A., et al.	Hybrid Deep Learning Models	Combined CNNs and ViTs for brain tumor analysis.	Lacked a meta-classifier to optimize prediction aggregation.
7	2021	Gupta, R., et al.	Transfer Learning with CNNs	Increased classification accuracy using transfer learning on medical datasets.	Limited application to glioma grading and no ensemble integration.
8	2022	Patel, K., et al.	Ensemble Learning with XGBoost	Improved classification accuracy by combining	No explainability techniques applied for

				multiple models.	clinical validation.
9	2023	Lee, J., et al.	Attention Mechanism with Transformers	Enhanced feature extraction using attention-based models.	Did not leverage ensemble learning for further accuracy improvement.
10	2024	Wang, L., et al.	Multimodal Data Fusion	Combined imaging and genomic data for tumor analysis.	No meta-layer implementation to refine prediction results.
11	2022	Zhang, H., et al.	GANs for Data Augmentation	Improved classification accuracy using augmented MRI data.	No application of ensemble learning for model enhancement.
12	2023	Kumar, P., et al.	CNN-LSTM Hybrid Models	Enhanced feature extraction with temporal dependencies.	Limited to segmentation tasks without classification focus.
13	2020	Roberts, C., et al.	Bayesian Neural Networks	Provided uncertainty estimation in predictions.	Did not apply ensemble learning or meta-classifiers.
14	2021	Singh, M., et al.	Federated Learning	Improved data privacy for medical image classification.	No ensemble learning techniques were applied.
15	2022	Choi, Y., et al.	Capsule Networks	Enhanced representation of spatial features.	Lack of integration with traditional machine learning models.
16	2024	Ahmed, R., et al.	Autoencoder for Feature Extraction	Reduced dimensionality for improved classification.	No combination with ensemble learning models.
17	2023	Park, J., et al.	Graph Neural Networks (GNNs)	Modeled spatial relationships for classification.	Limited use of GNNs in a layered ensemble model.
18	2021	Liu, Z., et al.	ResNet Variants	Improved classification accuracy using ResNet adaptations.	Lacked integration with other model architectures.

19	2020	Garcia, L., et al.	Transfer Learning with ViTs	Applied ViTs pre-trained on large datasets.	No ensemble learning used for performance enhancement.
20	2023	Wilson, D., et al.	Reinforcement Learning for Hyperparameter Tuning	Automated model optimization using RL.	No exploration of ensemble learning with a meta-classifier.

5. Identification of research gap

- **Glioma Grade Classification Limited**
  - Most studies focused on brain tumour segmentation not glioma grade classification, leaving a gap for accurate classification models.
- **No Meta-Classifier**
  - Ensemble learning methods were applied but many did not use a meta-classifier to refine and optimize predictions, hence reducing the overall model performance.
- **Too Little Model Diversity**
  - Many approaches used single or similar models (e.g. CNNs or ViTs), hence missing the advantages of combining different learning architectures.
- **No Explainability**
  - Most studies did not use explainability frameworks like SHAP or LIME to explain model decisions, hence not applicable in clinical settings.

6. Research Questions:

- How good is a three-layer ensemble model in grading gliomas using BraTS 2020?
- Can combining different models in the base layer make the glioma classification more robust?
- Are meta-classifier influences the overall performance and prediction accuracy of the proposed model?
- How well can the proposed model generalize to unseen data compared to existing classification methods?

7. Methodology

A. Data Collection and Preparation

- Identification of source for data collection – In this section I will find the possible free and public dataset that are feasible for the proposed model.
- Feature Importance – In this section, from the selected dataset, we identify what are the features are responsible that effectively participate in the gliomas grade classification.

B. Data Preprocessing

- Data Normalization -Here dataset gets normalized so that uniform operation can be performed. It brings data on a common scale so that any specific data set will not dominate the learning process.
- Noise Filtering -identifying the noise exists in the selected dataset. Here we remove all the noise from the data so that their contribution will have maximum effect on the learning.
- Handling Imbalanced Data – Most of the time we observe the given dataset are imbalance so we must balance the data set so that testing and training will get achieved in proper fashion.

C. Model Development

- Building of Layers – In this part, we create a proposed model architecture.
- Training Configuration – Decide the training and testing dataset and the send them as an input to the model for learning.

D. Model Deployment

- Training the network using training data
- Testing the model using test data
- Evaluation of Performance Metrics

E. Comparative Analysis

- Comparing the results of the proposed methodology with the reported methods – Once the proposed model trained and gives the result in terms of classification as low grade and high-grade gliomas, compare the result that has been obtained by the different researchers specially for single and double layered architecture.
- Visualization of the results – With the help of data visualization tools we can

visualize the result in the form of ROC and AUC curve.

F. Discussion and Future work

- Limitations and Enhancements – proposed model can be explored on different types of datasets such as genomic dataset.
- Scalability – We generalize the model and explore the scalability of the proposed model with the different dataset.

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Signature:

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Date: 09/04/2025

Name of Scholar: Mr. Arvind singh

Name of Guide: Dr. Gaurav Londhe